The Issue of Robustness in the Acquisition of Relocatable Targets – An Overview

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1 INTRODUCTION

Features are a means of statistical pattern recognition that ATR algorithms use to discriminate ground targets from the surrounding clutter background and, subsequently, to sort potential targets into one of several target classes (including the non-target case). Problems for ATR arise from the specular nature of radar imagery because small changes to the configuration of targets can result in significant changes to the resulting target signature [3][4]. This adds to the challenge of constructing a classifier that is both robust to changes in target configuration and target aspect, and which is capable of generalizing to previously unseen targets.

ATR features have to provide at the same time good inter-class separability and good intra-class stability. The reference vectors usually are obtained from former measurements of the respective target either on a turntable or by means of SAR and are stored in look-up tables. The test vectors are obtained on-line while the seeker is passing over the target area. In order for the ATR to provide reliable results both the test vectors and the reference vectors have to show **robustness** against target modifications, preferably including camouflage, different target realizations or articulations, slight changes in depression angle, aspect angle changes that occur during the time-on-target, and many more.

It has been shown [12] that the statistics of the test and reference vectors normally are not constant under all these variations, one of the strongest influences being the aspect angle dependence. Therefore, enhancing the robustness of an ATR scheme has to be understood in the sense that these changes are taken into account appropiately, and that the estimates that are obtained of these vectors are representative for the varying statistics. As a consequence, the classification performance should not be degraded.

In order to obtain the desired robustness it is of great importance to eliminate those target variations that can be handled beforehand, the most crucial one being the aspect angle dependence. The analysis of tower/turntable measurements on typical targets shows that feature values as a function of aspect angle do not only fluctuate around a stable mean, but that their statistics themselves, i.e. mean and standard deviation, are a function of aspect angle. It has been demonstrated before how important an independent determination of the target aspect angle is. More details are given in chapter 5.

An important issue is how to describe robustness quantitatively, i.e. to define some “figure of merit” (FOM). Such a FOM cannot only be used to compare different ATR approaches, its main strength lies in the possibility to optimize a given approach by varying certain free parameters, and also in the possibilty to select the most powerful features out of a given set of features.

During the past years, SET069 proposed and anylysed several different FOMs to assess robustness. They will be summarized and discussed in the following.

Essentially, there are two main approaches that have to be compared:

- the separability between feature histograms (using the Kolmogoroff-Smirnow distance as a distance measure)
- analysis of confusion matrices based on a generic classification scheme

Typical features of various types (geometric, statistical, polarimetric, scatterer power, structural etc.) were used, each one depending on one or two parameters that allow optimization.

Two more topics that have to be addressed are how the feature reference vector can be constructed when measurements of more than one articulation are available, and the influence of an independent aspect angle determination.

The paper is organised in four sections. As most of the analysis is based on one data set, the first section gives a short description of the measurement setup and of the data used. In the second, the features used for classification are described in some detail. In the main section the relationship between robustness and inter-class separability is analysed. Also, it is shown how confusion matrices

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can be used to characterize robustness. Finally, some results on the aspect angle behaviour of the features are presented.

2 DESCRIPTION OF THE TOWER/TURNTABLE DATA

For the measurements that are analysed here, the FGAN operated fully polarimetric MEMPHIS radar [8] was located on top of a tower at a height of 47 meters. The three targets (T72, ZSU 23-4 and BMP) were positioned on a turntable at a distance of about 154m, giving rise to a slant range of 161m and a depression angle of 17°.

The MEMPHIS 35 GHz radar transmitted linear V polarisation, and received H and V simultaneously thus providing orthogonal VV and VH channels. The basic waveform is a linear chirp with 200 MHz bandwidth. In order to achieve higher range resolution, this chirp is combined with a stepped frequency mode with 8 steps of 100 MHz increment [9]. The resulting maximum processing bandwidth thus is 800 MHz. However, as this requires a 320-point DFT (2.5 MHz frequency sampling step), here only a reduced bandwidth of 640 MHz was processed allowing the use of a 256-point FFT. The resulting range resolution is about 0.24m which is sufficient for this kind of ATR analysis [10].

A full revolution of the turntable took place in 130 seconds, the effective PRF was $2300s^{-1}/8$ such that a 128-point Doppler FFT results in a cross-range resolution of 0.2m, sufficiently close to the desired square-pixel case. The targets were measured in the following configurations: the turret of the T-72 was positioned 20° to the left, and in 30° intervals from 0° (forward) to 180° (backward). In the case of the ZSU 4 different and of the BMP 5 different combinations of shut/closed driver's, commander's and turret hatches were realized, cf.[6]. The positioning on the turntable remained unchanged from one articulation to the next. All data underwent an identical polarimetric calibration to warrant optimal comparability.

3 A SET OF GENERIC CLASSIFICATION FEATURES

All feature values were computed on the basis of 2-D ISAR images with 0.24m (range) by 0.2m (cross-range) pixels. They were taken from a list prepared by the NATO SET-TG14 working group [7]. For geometrical, statistical, and structural features, the total power map ($|VV|^2 + |VH|^2$) was used, for the polarimetric features the VV and VH power map were used in parallel.

- ft1 = range extent of 20 strongest scatterers
- ft2 = cross-range extent of 20 strongest scatterers
- ft3 = ft1*ft2 (= area of the "minimum bounding rectangle" (MBR))
- ft4 = mean/std.dev.(total power|MBR)
- ft5 = (powersum 10 strongest scatterers) /powersum(MBR)
- ft6 = log10(pmax(1)/pmax(5)) (ratio between strongest and 5th strongest scatterer within the MBR)
- ft7 = log10(pmax(1)/pmin)|MBR (ratio between strongest and weakest scatterer within the MBR)
- ft8 = $\max(pvv/pvh)|_{dB} - \min(pvv/pvh)|_{dB}$ (span of parallel/cross channel separation)
- ft9 = $\mathrm{slope}(pmax\ vs.dif)|_{dB}$
- ft10 = $\mathrm{shift}(pmax\ vs.dif)|_{dB}$

(in ft9 and ft10 "pmax" stands for the 10 strongest scatters within the MBR, sorted in descending order, "dif" contains the related channel differences pvv/pvh, shift and slope refer to a least squares line fit that is applied to these 10 pairs of values).

The rationale for the selection of this set of features is not that they constitute a "best" set. Rather they are considered to be a "generic" set with representatives from several feature types, namely geometric, statistical, scatterer power related or structural, and polarimetric. Of course, some of these features are more or less correlated with one another. This can be assessed either by determining all the mutual cross correlation coefficients, or by a principal component analysis (PCA, [11]). Therefore, only certain subsets out of these 10 features will form meaningful sets of ATR features.

4 Two possible "Figures of Merit" to quantify robustness

Single features

A convenient way to compare two probability density functions (pdf's) or histograms is by determining the Kolmogoroff-Smirnov distance (KSD) which is defined as the maximum difference between the two pertinent cumulative distributions. By definition, the KSD can vary between 0 and 1, where "0" means identity, and "1" means complete separation. Let us now quantify the similarity between the pdfs of different target articulations by means of the KSD. This is best done using a table that lists all possible combinations of pairs of targets for a selected feature. Let us again look at feature # 10 (Table 1). The KSD between pairs of different T72 are fairly low, mostly less than 0.08 and hence close to zero as required.

For pairs of ZSU or BMP, values can be as high as 0.13 which is quite high and suggests major differences. In the areas that are dark grey-shaded we have pairs of different target types. Here, in the ideal case we would expect values close to 1, i.e. complete separation. Of course, this is not the case, rather the values are around 0.2 to 0.3, hardly above 0.35. This is certainly not satisfactory, but one has to keep in mind that the classification will not be done with only one feature but that one will go to higher dimensions of the feature space where less overlap is expected.

	T72b	T72c	T72d	T72e	T72f	T72g	T72h	ZSUa	ZSUb	ZSUc	ZSUd	BMPa	BMPb	BMPc	BMPd	BMPe
T72a	0.077	0.058	0.086	0.064	0.064	0.056	0.103	0.228	0.167	0.125	0.139	0.297	0.286	0.3280	0.211	0.214
T72b	0	0.069	0.072	0.114	0.061	0.058	0.081	0.192	0.122	0.075	0.097	0.242	0.233	0.261	0.15	0.167
T72c		0	0.077	0.1	0.042	0.047	0.064	0.211	0.164	0.097	0.125	0.269	0.264	0.289	0.181	0.189
T72d			0	0.081	0.067	0.061	0.064	0.189	0.128	0.083	0.097	0.261	0.253	0.286	0.172	0.178
T72e				0	0.103	0.094	0.108	0.2	0.161	0.117	0.139	0.261	0.247	0.281	0.172	0.192
T72f					0	0.047	0.067	0.211	0.139	0.083	0.111	0.267	0.253	0.286	0.178	0.186
T72g						0	0.058	0.197	0.144	0.094	0.103	0.253	0.244	0.281	0.167	0.172
T72h							0	0.161	0.114	0.075	0.081	0.217	0.222	0.247	0.144	0.156
ZSUa								0	0.092	0.133	0.119	0.122	0.142	0.142	0.058	0.064
ZSUb									0	0.086	0.072	0.161	0.142	0.194	0.078	0.075
ZSUc										0	0.05	0.192	0.181	0.214	0.108	0.111
ZSUd											0	0.181	0.203	0.206	0.097	0.119
BMPa												0	0.031	0.047	0.108	0.097
BMPb													0	0.061	0.108	0.089
BMPc														0	0.125	0.131

Table 1: *Kolmogoroff-Smirnov distances between all possible pairs of histograms, feature #10*

The shaded areas of the triangular matrix $\underline{\mathbf{K}}$ designate where KSD values close to "1" are expexted, all others should be close to zero. If we define a reference matrix $\underline{\mathbf{R}}$ which contains only the desired values 0 or 1 in the appropriate positions, then the quality of a feature can be judged by computing the distance between the actual matrix and the reference.

$$d = \sqrt{\frac{2}{17 \cdot 16} \sum_{i<j} \| K - R \|^2}$$

Table 2 shows an example. The smaller this value is the closer the measured matrix is to the reference. Taking this metric, the range extent (feature 1) performs best.

However, this single value does no longer allow to differentiate between robustness and separability. Robustness is the better the closer the **intra class** KSDs are to zero, and separability is the better the closer the **interclass** KSDs are to 1. One can therefore average all intra class KSDs (resulting in K_0) and all interclass KSD (resulting in K_1) and plot the results in K_0-K_1-coordinates, cf. Figure 2). The closer a feature is located to the point (0,1) the better its performance will be. As one recognizes, none of the 10 features comes close to this ideal, there seems to be even a certain proportionality between K_0 and K_1 for higher values. However, for all features except #8, K_1 is larger than K_0, as it should be. Most pronounced we find this for features 2, 3, 5, 6, 9 and 10.

Thus, one can try to optimize features (which usually depend on at least one free parameter) by minimizing either "d" or the distance to the point (0,1) in the K_0-K_1-diagramme.

Feature #	d
1	.55
2	.68
3	.583
4	.647
5	.635
6	.695
7	.638
8	.758
9	.68
10	.68

Table 2: *mean difference "d" between matrices* $\underline{K}$ *and* $\underline{R}$

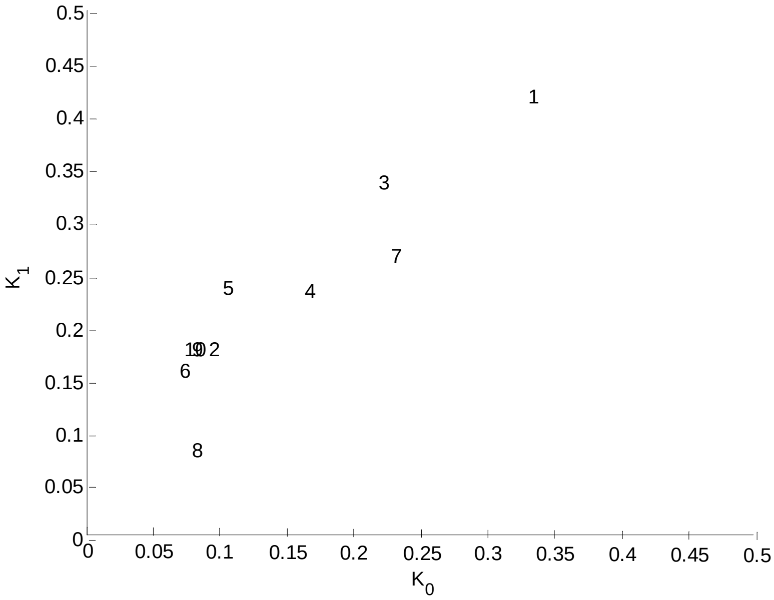

Figure 2: K_1 *vs.*K_0 *for features 1 through 10*

SETS OF SEVERAL FEATURES

Another means to assess feature robustness is to apply a generic classification scheme to the available data and determine the probabilities of correct classification (P_{cc}) for certain sets of features. For this purpose one has to create reference feature vectors (or training data) for all available targets or target types. Then a target under test is chosen, a test feature vector determined, and the Euclidian distance

$$d_{eukl}(\alpha) = \sqrt{\sum_{i=1}^{N} \frac{(f_i(\alpha) - F_i^{ref}(\alpha))^2}{\sigma_i^2}}$$

in feature space computed between this test vector and all reference vectors. The target under test for this special feature vector then gets the label of the reference target to which its distance is minimum. This is repeated for a large number of test vectors of the respective target under test (either from a limited aspect angle interval or - as in our examples - from all aspect angles between 0° and 360°), the scores being summed up for all reference categories. The P_{cc} values finally are determined as the ratio between the individual scores and the total number of test vectors. In this simple implementaion, we can talk of a "forced decision classifier" because the non-target case is not taken into account.

Out of the 10 features analysed here, subsets of only a few of them were formed for classification purposes. The main requirement for feature selection is that they carry independent information, i.e. are statistically independent. There are several ways to achieve this goal. A common one is the principal component analysis (PCA) where, dependent on the eigenvalues of the covariance matrix, only the most "meaningful" features or linear combinations of features are retained. Another, simpler way is to determine the cross-correlation coefficients for all possible pairs of features, and then select only those sets that are essentially uncorrelated. The feature sets analysed in the folowing are the result of this latter procedure.

How can one create reference feature vectors? For this purpose we refer to results from former analyses [6],[7] that demonstrated the importance of an independent determination of the orientation of the target under test. Thus, comparison has only to be done to reference feature vectors out of a limited aspect angle interval instead of [0°, 360°] which considerably increases the classification performance. An achievable value for the precision of pose estimation is 10° to 20° or even better. Therefore, a sliding window averaging was applied to the original features over a ±10° interval with respect to each aspect angle thus creating the pertinent reference value. Fig.3 shows the effect of this averaging

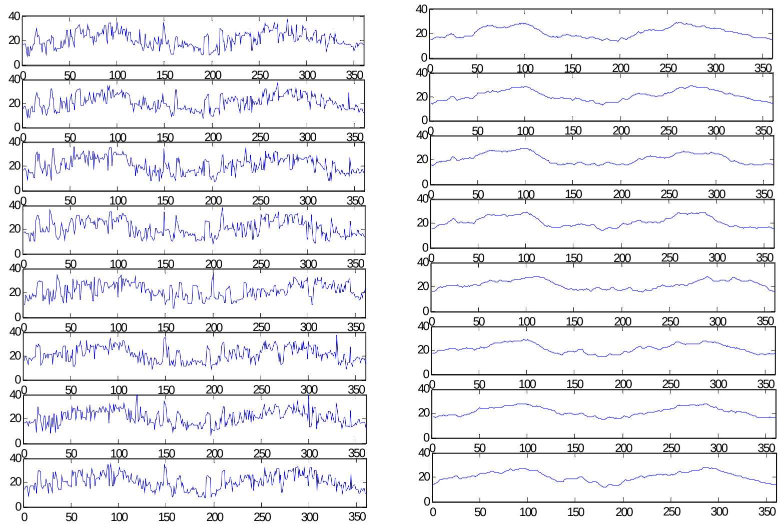

Figure 3: *Feature 2 (cross-range extent for 8 T72, test values (left) and reference values (right)*

Table 3 shows the results for a set of features comprising features 2, 4, 6, 8 and 10. The separation into test data and training data is done in such a way that one file is selected which is to be tested. Then it is compared against all 17 averaged references (training data) including itself for comparison. Consequently, the columns show all 17 targets in their function as reference targets, whereas the rows of this confusion matrix **C** stand for the 17 objects as they are used one after the other as test targets. Feature vectors were taken from a full 360° revolution of the turntable, the corresponding reference vectors were selected at the same aspect angle as the test vector, the uncertainty of the pose estimate being reflected by the +/- 10° averaging.

What we expect ideally in this confusion matrix is that it shows values of $1/N_k$ in N_k x N_k-submatrices for the target type "k" that occurs in N_k different articulations, and zero in all other areas. This is because a robust classification scheme should treat all articulations of one target type in the same way resulting in a probability of classification of $1/N_k$ independent of which articulation is tested against which other one. This ideal reference matrix **R** can be used to establish a metric

$$D=\| \underline{\mathbf{C}}-\underline{\mathbf{R}}\|^2$$

that describes the performance of the feature set under consideration. It can be used to optimize the features by minimizing D with respect to the free parameters that occur in the feature definitions.

Based on the above reasoning, we expect 12.5% in the first block, 25% in the second, and 20% in the third one. We see that in our example the performance is far from perfect.

	T72a	T72b	T72c	T72d	T72e	T72f	T72g	T72h	ZSUa	ZSUb	ZSUc	ZSUd	BMPa	BMPb	BMPc	BMPd	BMPe
T72a	23.3	11.4	7.8	8.3	4.7	5.6	8.3	5.3	3.9	3.3	4.4	1.7	1.1	1.7	0.6	4.4	4.2
T72b	12.5	24.4	11.9	5.3	5.8	3.9	5.8	5.8	2.8	2.2	3.3	2.2	2.5	2.8	3.1	1.9	3.6
T72c	4.4	7.2	25.6	7.5	10	6.1	5.6	4.2	5	6.7	4.4	2.8	0.6	2.2	2.2	2.8	2.8
T72d	5.3	5	8.9	22.5	9.2	7.5	8.1	4.4	5	6.1	5	4.2	1.1	2.2	1.7	2.5	1.4
T72e	4.7	5.6	7.8	7.8	29.7	8.9	4.7	4.2	2.2	6.4	4.7	2.2	1.1	2.8	2.5	0.8	3.9
T72f	6.7	5.3	7.5	10.6	9.4	19.2	8.1	3.9	4.7	6.4	5.3	3.9	1.1	1.4	1.7	3.1	1.9

T72g	7.5	7.8	4.7	8.1	9.4	7.5	19.2	5.8	4.7	8.3	4.2	2.2	1.9	2.2	2.5	1.7	2.2
T72h	8.1	10.3	7.2	6.7	7.5	7.2	6.7	15.3	5.3	4.7	4.2	3.3	1.7	2.8	1.1	2.8	5.3
ZSUa	2.2	1.9	7.2	6.1	6.7	4.4	4.2	1.1	26.4	5.8	14.7	9.7	1.7	0.8	1.9	1.1	3.9
ZSUb	1.7	1.1	4.4	3.3	5	4.2	5	1.7	5	54.7	4.4	1.9	1.7	0.8	1.1	0.8	3.1
ZSUc	1.9	2.2	4.2	9.7	6.4	4.2	2.2	2.5	13.9	6.4	23.1	11.4	1.4	4.2	2.8	0.6	3.1
ZSUd	2.5	1.4	7.5	9.7	5	4.7	2.2	1.7	14.4	5	19.7	14.7	2.2	2.5	2.2	1.9	2.5
BMPa	2.8	2.8	2.5	3.1	8.1	6.1	5.3	3.3	6.9	4.7	7.2	3.3	12.5	11.4	9.2	3.6	7.2
BMPb	1.4	5.6	3.6	3.1	8.3	4.7	6.7	3.1	6.1	4.2	6.1	3.6	8.1	18.1	6.4	3.6	7.5
BMPc	2.2	3.3	3.1	3.3	9.7	7.8	6.1	4.4	5.3	6.4	6.4	2.2	9.2	11.1	11.4	1.9	6.1
BMPd	3.9	8.6	4.4	3.6	7.8	4.4	3.9	6.7	4.4	1.9	5.8	0.6	2.2	5	3.6	16.9	16.
BMPe	3.6	7.8	4.4	1.9	6.9	5	7.5	8.1	3.9	2.5	4.2	1.1	1.4	8.1	5.3	10	18.

Table 3: *probabilities of correct classification (%) for set of features 2,4,6,8 and 10*

5 INDEPENDENT DETERMINATION OF THE TARGET ASPECT ANGLE

It has been demonstrated before [1][2] how important an independent determination of the target aspect angle is. Among the methods most commonly used are the Hough transform or a process of pattern matching [1] [5].

For certain features, especially geometric ones like range and cross-range extent, it is clear that they will vary as a function of aspect angle. For others, like statistical or polarimetric features, it is not clear what behaviour to expect, although an aspect angle dependence should be anticipated in every case.

An example is shown in fig.4 where a typical statistical feature (f4) is represented. F4 is defined as the ratio between mean and standard deviation of the 20 strongest scatterers belonging to the target, its area being declared to be the “minimum bounding rectangle” (MBR) within each 2-d ISAR image. These ISAR images are processed with angular increments of about 1/40 of a degree (as a cross-range resolution of 0.2m at 35GHz requires an angular increment of 1.2°, this means overlapping ISAR processing). Thus, an aspect angle interval of 12° which may be assumed to be a typical value for the precision with which the target orintation can be determined, gives rise to about 500 templates. The resulting feature values are transformed into a histogram which represents the f4 statistics at the respective aspect angle. Fig.4 shows the full series of histograms between 0° and 360°. As one sees, the statistics of f4 is by no means constant.

The difference between two probability density functions can again be characterised by means of the KSD. Fig.5 shows this KSD between the overall pdf of f4 (out of 360°) and the “local” pdf’s as a function of aspect angle. The deviation in this example can be as high as 0.5!

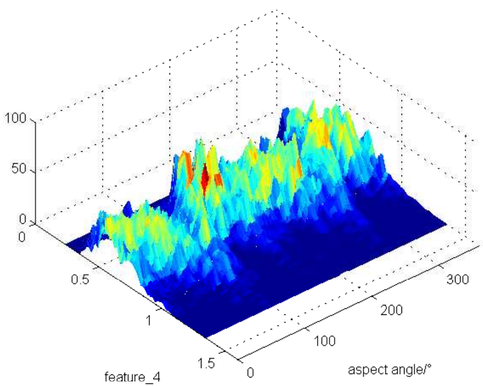

Fig.4 *feature #4 histograms for sliding window*

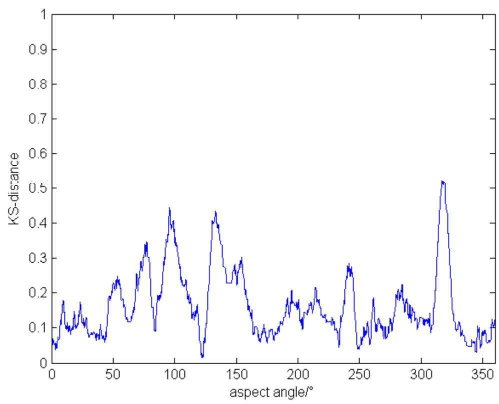

Fig.5 *KS distance between global and local f4 pdf‘s*

By applying a generic ATR scheme as described above, we can quantitatively assess the aspect angle dependence of the classification performance. For this purpose, the width “w” of the aspect error interval was varied between 0° and 10° in 50 steps of 0.2°. The P_{cc} (probability of correct classification) values were determined as a function of “w” by dividing the number of assignments per class by the total number (1800) of classifications per 360° aspect angle range.Let us first look into the NN results. A typical result is shown in fig.6 where one of the seven T72 is tested against the 3 classes. P_{cc} starts around 55% for the smallest “w” (i.e. most precise determination of target orientation) and drops to 43% at w=10°. The correct choice of the T72 (highest P_{cc}) is maintained for all interval sizes.

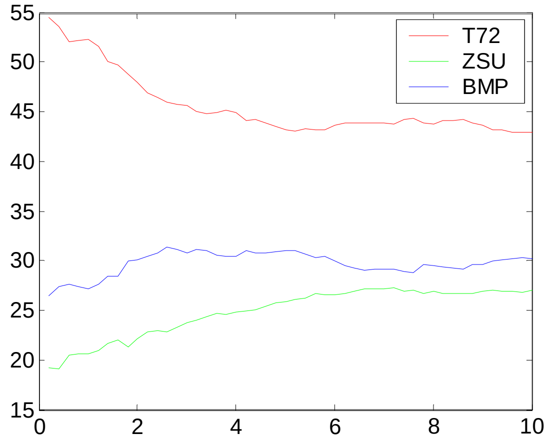

Fig.6 *P_{cc} of T72 tested against T72 (top), BMP(middle) and ZSU(bottom), features 2&7*

SUMMARY AND CONCLUSIONS

Three target types, namely T72, ZSU 23-4 and BMP-2 were measured in a tower/turntable configuration in 8, 4 and 5 articulations, respectively. Based on 2-D ISAR images in the VV and VH channel, a set of 10 geometric, statistical, structural and polarimetric features was calculated which was used to study the robustness of classification. The Kolmogoroff-Smirnov distance measure between histograms (pdf’s) was used to define a metric that at the same time allows to quantify intra-class robustness and inter-class separability for an individual feature. For sets of several features, a simple classification approach in connection with a reference confusion matrix allows to assess the robustness of classification. At the same time this reference matrix can be used to maximize robustness by varying the free parameters of the feature definitions such that the difference of the measured confusion matrix with respect to the reference matrix is minimized. It was found that the number of scatterers N_{sc} does not offer a good potential for optimization.

As to choosing an appropriate reference feture vector, it could be demonstrated further, that averaging this reference over all available target articulations improves the classification performance as compared to a reference that is based on one articulation only.

Finally, it was demonstrated that the feature statistics may be strongly dependent on the aspect angle of the target. As a consequence, the ATR performance has to be improved by independently determining the target orientaion, e.g. by means of a Hough transform or pattern matching. In order to demonstrate the importance of an independent pose estimation of the target under test, reference feature vectors were computed as sliding window averages over up to +/-10° aspect intervals. The normal case is that the smaller the aspect angle uncertainty interval, the higher is the probability of correct classification while the false alarm rates (competing vehicles) at the same time are decreased. Exceptions of this general behaviour may exist, however.

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The Issue of Robustness in the Acquisition of Relocatable Targets – - an Overview

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Overview

- Introduction
- Description of the ISAR data
- The target array
- ATR features used for classification
- The Kolmogorov-Smirnow distance for single features
  - Intra-class stability vs. inter-class separabilty
- Classification results for sets of features
  - Construction of feature reference vectors
  - Confusion matrices
- Independent determination of the target aspect angle
- Summary and conclusions

Introduction

- ATR features have to provide at the same time good inter-class separability and good intra-class stability
- both the test vectors and the reference vectors have to show **robustness** against target modifications, preferably including:
    - camouflage,
    - different target realizations or articulations,
    - slight changes in depression angle,
    - aspect angle changes that occur during the time-on-target, etc.
- The quantitative description of robustness requires to define some "figure of merit" (FOM).

Suggestions for FOMs to quantify feature robustness

Two approaches will be compared:

- the separability between feature histograms (using the Kolmogoroff-Smirnow distance as a distance measure)
- analysis of confusion matrices based on a generic classification scheme

The usefulness of FOMs

- compare different ATR approaches
- optimize a given approach by varying certain free parameters
- possibilty to select the most powerful features out of a given set of features

The Target set

The FGAN operated fully polarimetric MEMPHIS radar was located on a tower at a height of 47 meters. The three targets (T72, ZSU 23-4 and BMP) were positioned on a tilted turntable at a distance of about 154m, giving rise to a slant range of 161m and a depression angle of 20°.

The targets were measured in the following configurations:

- the turret of the T-72 was positioned 20° to the left, and in 30° intervals from 0° (forward) to 180° (backward).
- 4 different (ZSU) and 5 different (BMP) combinations of shut/closed driver's, commander's and turret hatches were realized

The target positioning on the turntable remained unchanged from one articulation to the next

The ISAR data

- The MEMPHIS 35 GHz radar transmitted linear V polarisation, and received H and V simultaneously thus providing orthogonal VV and VH channels.
- The basic waveform is a linear chirp with 200 MHz bandwidth combined with a stepped frequency mode with 8 steps of 100 MHz increment. The resulting maximum processing bandwidth thus is 800 MHz. (320-point DFT, 2.5 MHz frequency sampling step)
- here only a reduced bandwidth of 640 MHz was processed (256-point FFT). The resulting **range resolution is about 0.24m**
- A full revolution of the turntable lasted 130 seconds, the effective PRF was $2300 s^{-1}/8$ such that a 128-point Doppler FFT results in a **cross-range resolution of 0.2m**

ATR features used for classification

- ft1 = range extent of 20 strongest scatterers
- ft2 = cross-range extent of 20 strongest scatterers
- ft3 = ft1*ft2 (= area of the "minimum bounding rectangle" (MBR))
- ft4 = mean/std.dev.(total power|MBR)
- ft5 = (powersum 10 strongest scatterers) /powersum(MBR)
- ft6 = log10(pmax(1)/pmax(5)) (ratio between strongest and 5^{th} strongest scatterer within the MBR)
- ft7 = log10(pmax(1)/pmin)|MBR (ratio between strongest and weakest scatterer within the MBR)
- ft8 = $\max(pvv/pvh)|_{dB}$ - $\min(pvv/pvh)|_{dB}$ (span of parallel/cross channel separation)
- ft9 = $\text{slope}(\text{pmax vs.dif})|_{dB}$
- ft10 = $\text{shift}(\text{pmax vs.dif})|_{dB}$

Geometric
Statistical
Structural
polarimetric

Robustness FOM for single features

A convenient way to compare two probability density functions (pdf's) or histograms is to determine the Kolmogoroff-Smirnov distance (KSD)

The KSD is defined as the maximum difference between the two pertinent cumulative distributions.

By definition, the KSD can vary between 0 and 1, where "0" means identity, and "1" means complete separation

KSD results

	T72b	T72c	T72d	T72e	T72f	T72g	T72h	ZSUa	ZSUb	ZSUc	ZSUd	BMPa	BMPb	BMPc	BMPd	BMPe
T72a	0.077	0.058	0.086	0.064	0.064	0.056	0.103	0.228	0.167	0.125	0.139	0.297	0.286	0.3280	0.211	0.214
T72b	0	0.069	0.072	0.114	0.061	0.058	0.081	0.192	0.122	0.075	0.097	0.242	0.233	0.261	0.15	0.167
T72c		0	0.077	0.1	0.042	0.047	0.064	0.211	0.164	0.097	0.125	0.269	0.264	0.289	0.181	0.189
T72d			0	0.081	0.067	0.061	0.064	0.189	0.128	0.083	0.097	0.261	0.253	0.286	0.172	0.178
T72e				0	0.103	0.094	0.108	0.2	0.161	0.117	0.139	0.261	0.247	0.281	0.172	0.192
T72f					0	0.047	0.067	0.211	0.139	0.083	0.111	0.267	0.253	0.286	0.178	0.186
T72g						0	0.058	0.197	0.144	0.094	0.103	0.253	0.244	0.281	0.167	0.172
T72h							0	0.161	0.114	0.075	0.081	0.217	0.222	0.247	0.144	0.156
ZSUa								0	0.092	0.133	0.119	0.122	0.142	0.142	0.058	0.064
ZSUb									0	0.086	0.072	0.161	0.142	0.194	0.078	0.075
ZSUc										0	0.05	0.192	0.181	0.214	0.108	0.111
ZSUd											0	0.181	0.203	0.206	0.097	0.119
BMPa												0	0.031	0.047	0.108	0.097
BMPb													0	0.061	0.108	0.089
BMPc														0	0.125	0.131

Example: feature #10

The shaded areas of the triangular matrix **K** designate where KSD values close to “1” are expexted, all others should be close to zero

KSD based FOM

If we define a reference matrix **R** which contains only the desired values 0 or 1 in the appropriate positions, then the quality of a feature can be judged by computing the distance between the actual matrix and the reference matrix:

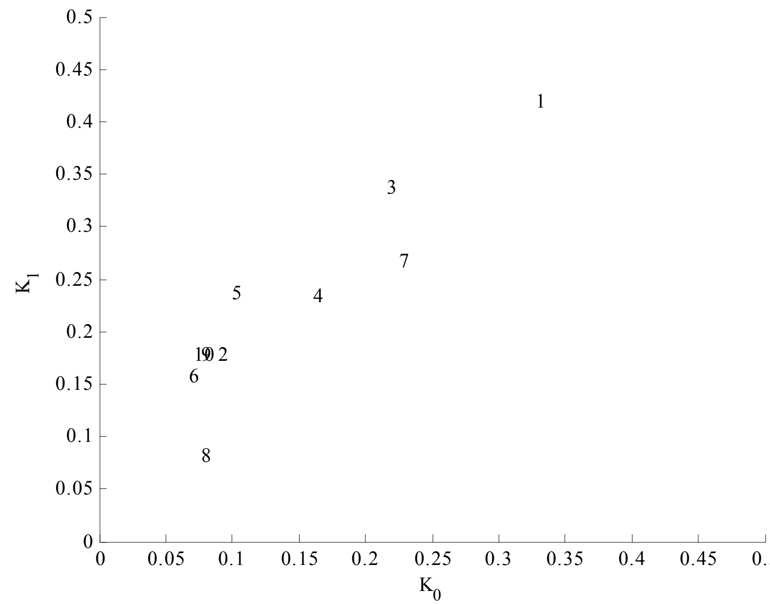
$$d = \sqrt{\frac{2}{17 \cdot 16} \sum_{i<j} \| K - R \|^2}$$

Feature #	d
1	.55
2	.68
3	.583
4	.647
5	.635
6	.695
7	.638
8	.758
9	.68
10	.68

Stability vs. separabilty

Robustness is the better the closer the **intra class** KSDs are to zero, and **separability** is the better the closer the **interclass** KSDs are to 1.

One can therefore average all intra class KSDs (resulting in K_0) and all interclass KSDs (resulting in K_1) and plot the results in K_0-K_1-coordinates. The closer a feature is located to the point (0,1) the better its performance will be.



Thus, one can try to optimize features (which usually depend on at least one free parameter) by minimizing either “d” or the distance to the point (0,1) in the K_0-K_1-diagramme.

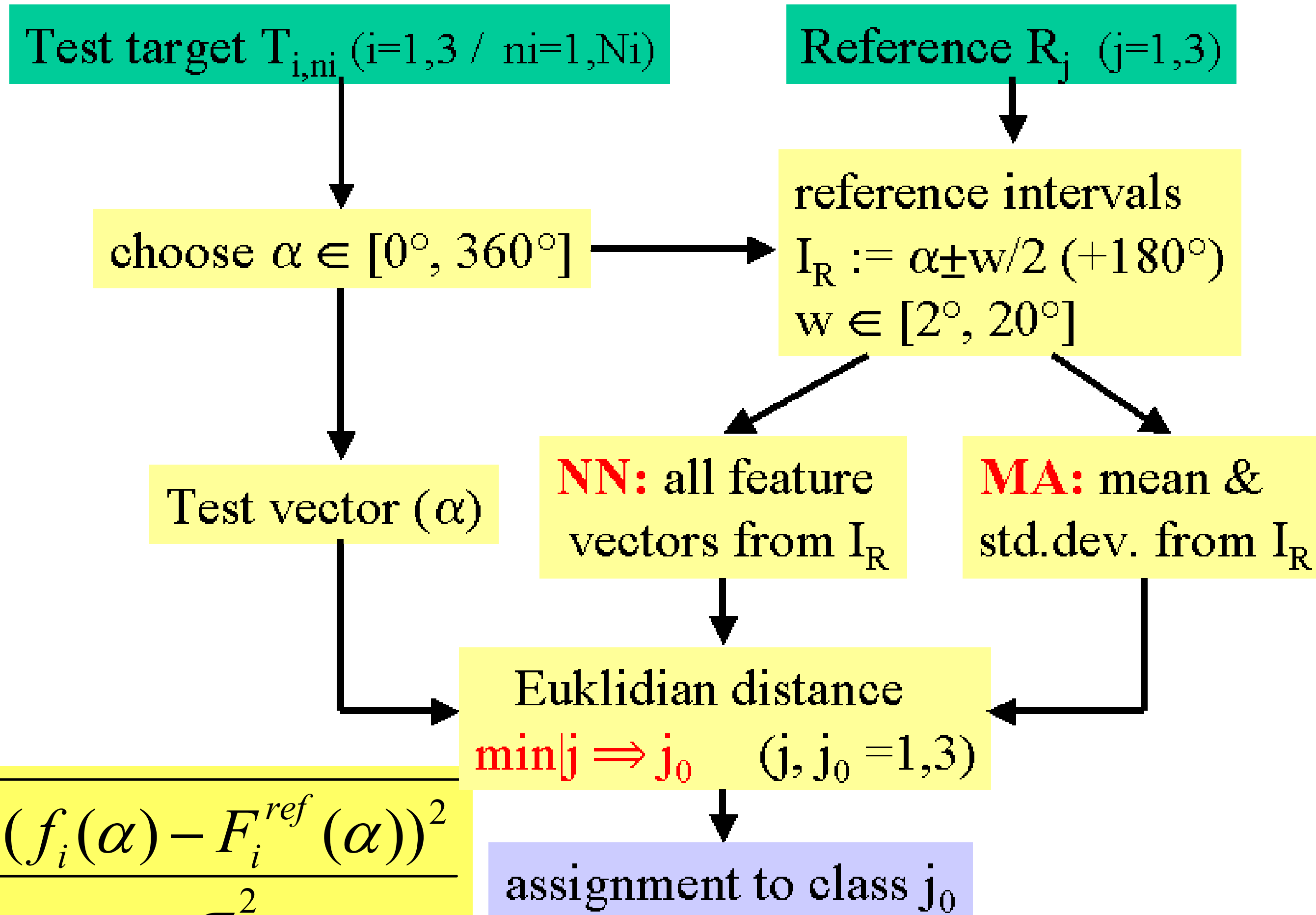
FOM for sets of several features

The main requirement for feature selection is that they carry independent information, i.e. are statistically independent.

This can be achieved by:

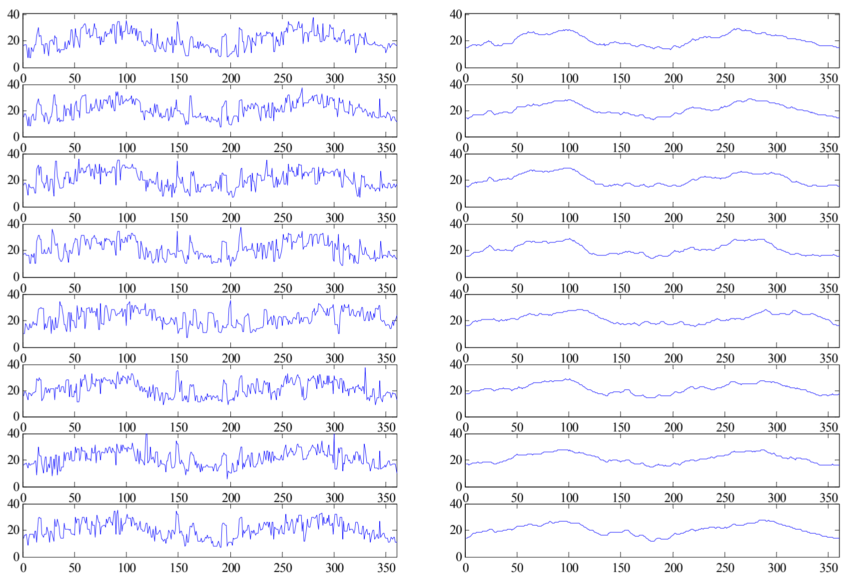
- **principal component analysis** (PCA): dependent on the eigenvalues of the covariance matrix, only the most “meaningful” features or linear combinations of features are retained.
- **cross-correlation coefficients** for all possible pairs of features: select only those sets whose features are essentially uncorrelated

A simple classification scheme



$$d_{eukl}(\alpha) = \sqrt{\sum_{i=1}^{N} \frac{(f_i(\alpha) - F_i^{ref}(\alpha))^2}{\sigma_i^2}}$$

Creating a feature reference



Feature 2 (cross-range extent for 8 T72, test values (left) and reference values (right)

Assume an independent determination of the orientation of the target under test with a the precision of pose estimation of 10° to 20° or even better

⇒ a sliding window averaging was applied to the original features over a ±10° interval with respect to each aspect angle out of [0°, 360°].

The Confusion Matrix

	T72a	T72b	T72c	T72d	T72e	T72f	T72g	T72h	ZSUa	ZSUb	ZSUc	ZSUd	BMPa	BMPb	BMPc	BMPd	BMPe
T72a	23.3	11.4	7.8	8.3	4.7	5.6	8.3	5.3	3.9	3.3	4.4	1.7	1.1	1.7	0.6	4.4	4.2
T72b	12.5	24.4	11.9	5.3	5.8	3.9	5.8	5.8	2.8	2.2	3.3	2.2	2.5	2.8	3.1	1.9	3.6
T72c	4.4	7.2	25.6	7.5	10	6.1	5.6	4.2	5	6.7	4.4	2.8	0.6	2.2	2.2	2.8	2.8
T72d	5.3	5	8.9	22.5	9.2	7.5	8.1	4.4	5	6.1	5	4.2	1.1	2.2	1.7	2.5	1.4
T72e	4.7	5.6	7.8	7.8	29.7	8.9	4.7	4.2	2.2	6.4	4.7	2.2	1.1	2.8	2.5	0.8	3.9
T72f	6.7	5.3	7.5	10.6	9.4	19.2	8.1	3.9	4.7	6.4	5.3	3.9	1.1	1.4	1.7	3.1	1.9
T72g	7.5	7.8	4.7	8.1	9.4	7.5	19.2	5.8	4.7	8.3	4.2	2.2	1.9	2.2	2.5	1.7	2.2
T72h	8.1	10.3	7.2	6.7	7.5	7.2	6.7	15.3	5.3	4.7	4.2	3.3	1.7	2.8	1.1	2.8	5.3
ZSUa	2.2	1.9	7.2	6.1	6.7	4.4	4.2	1.1	26.4	5.8	14.7	9.7	1.7	0.8	1.9	1.1	3.9
ZSUb	1.7	1.1	4.4	3.3	5	4.2	5	1.7	5	54.7	4.4	1.9	1.7	0.8	1.1	0.8	3.1
ZSUc	1.9	2.2	4.2	9.7	6.4	4.2	2.2	2.5	13.9	6.4	23.1	11.4	1.4	4.2	2.8	0.6	3.1
ZSUd	2.5	1.4	7.5	9.7	5	4.7	2.2	1.7	14.4	5	19.7	14.7	2.2	2.5	2.2	1.9	2.5
BMPa	2.8	2.8	2.5	3.1	8.1	6.1	5.3	3.3	6.9	4.7	7.2	3.3	12.5	11.4	9.2	3.6	7.2
BMPb	1.4	5.6	3.6	3.1	8.3	4.7	6.7	3.1	6.1	4.2	6.1	3.6	8.1	18.1	6.4	3.6	7.5
BMPc	2.2	3.3	3.1	3.3	9.7	7.8	6.1	4.4	5.3	6.4	6.4	2.2	9.2	11.1	11.4	1.9	6.1
BMPd	3.9	8.6	4.4	3.6	7.8	4.4	3.9	6.7	4.4	1.9	5.8	0.6	2.2	5	3.6	16.9	16.
BMPe	3.6	7.8	4.4	1.9	6.9	5	7.5	8.1	3.9	2.5	4.2	1.1	1.4	8.1	5.3	10	18.

The Confusion Matrix, cont'd

This confusion matrix is expected that to show values of $1/N_k$ in N_k x N_k-submatrices for the target type "k" that occurs in N_k different articulations, and zero in all other areas.

The reason is that a robust classification scheme should treat all articulations of one target type in the same way resulting in a probability of classification of $1/N_k$ independent of which articulation is tested against which other one.

This ideal reference matrix **R** can be used to establish a metric

$$D = \| \underline{\mathbf{C}} - \underline{\mathbf{R}} \|^2$$

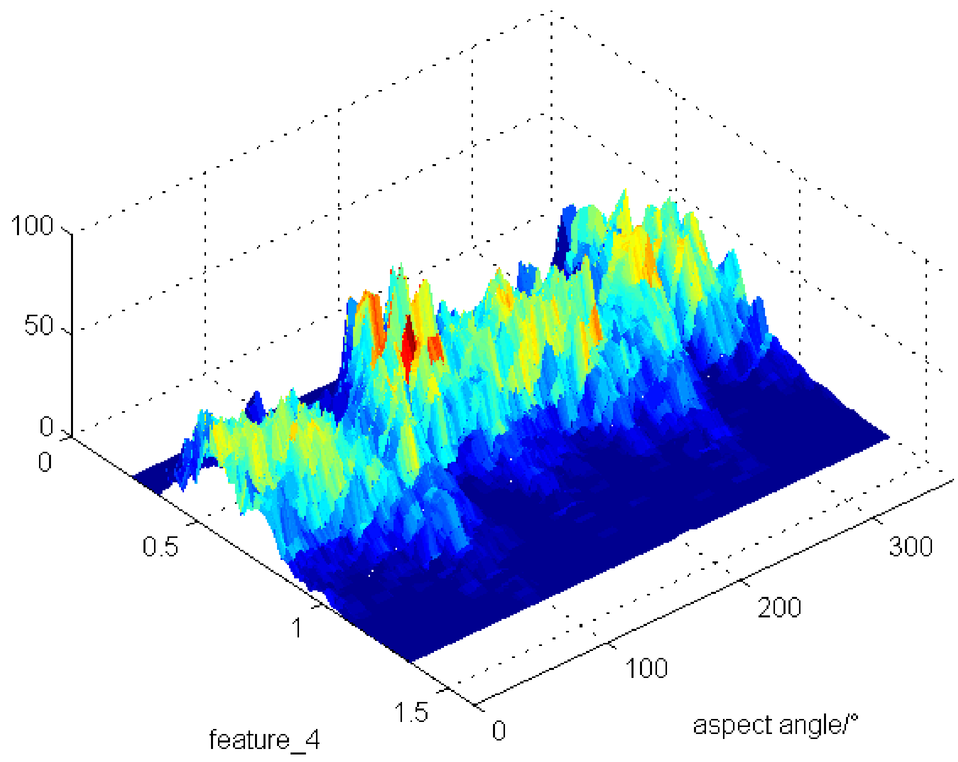
that describes the performance of the feature set under consideration.

It can be used to **optimize** the features **by minimizing D** with respect to the free parameters that occur in the feature definitions.

Independent determination of the target aspect angle

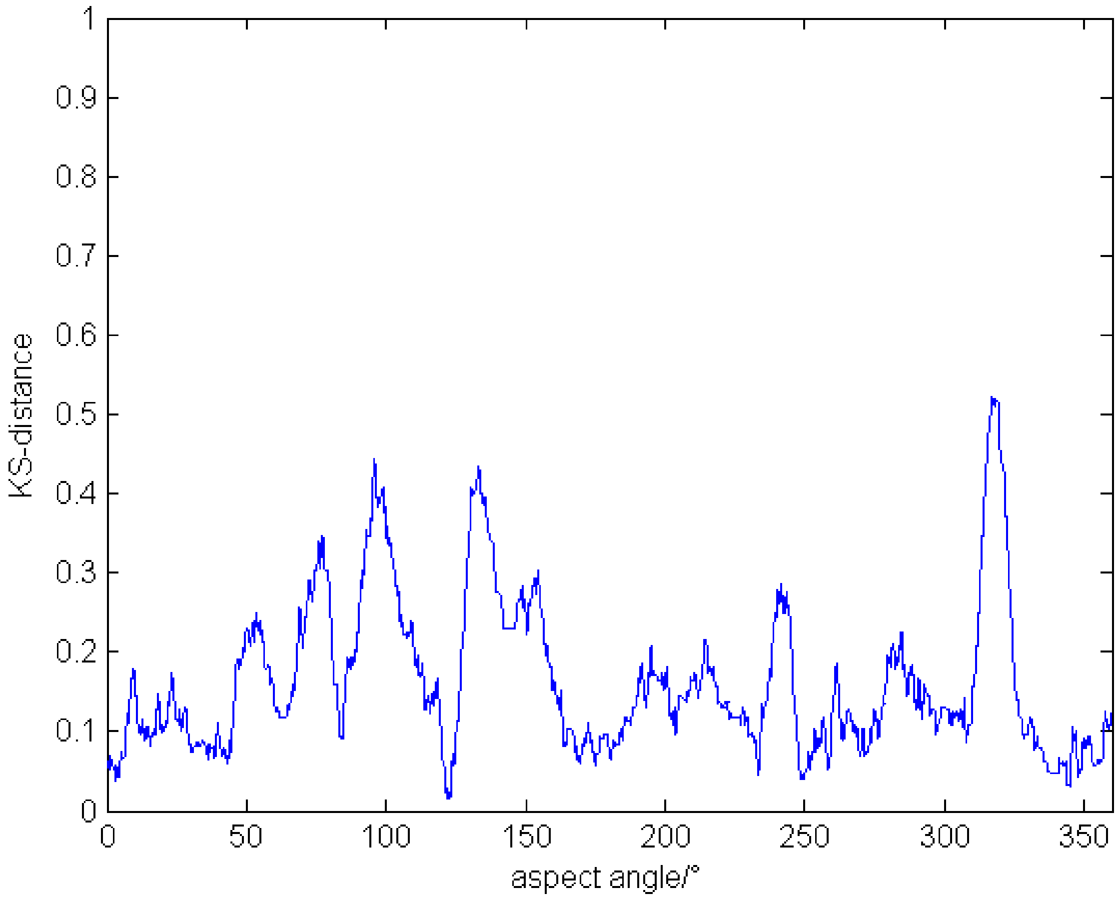
For certain features, especially geometric ones like range and cross-range extent, it is clear that they will vary as a function of aspect angle.
For others, like statistical or polarimetric features, it is not clear what behaviour to expect, although an aspect angle dependence should be anticipated in every case
Among the methods most commonly used are the Hough transform or a process of pattern matching
There always remains the front / rear ambiguity!

Local feature pdf's as a function of aspect angle



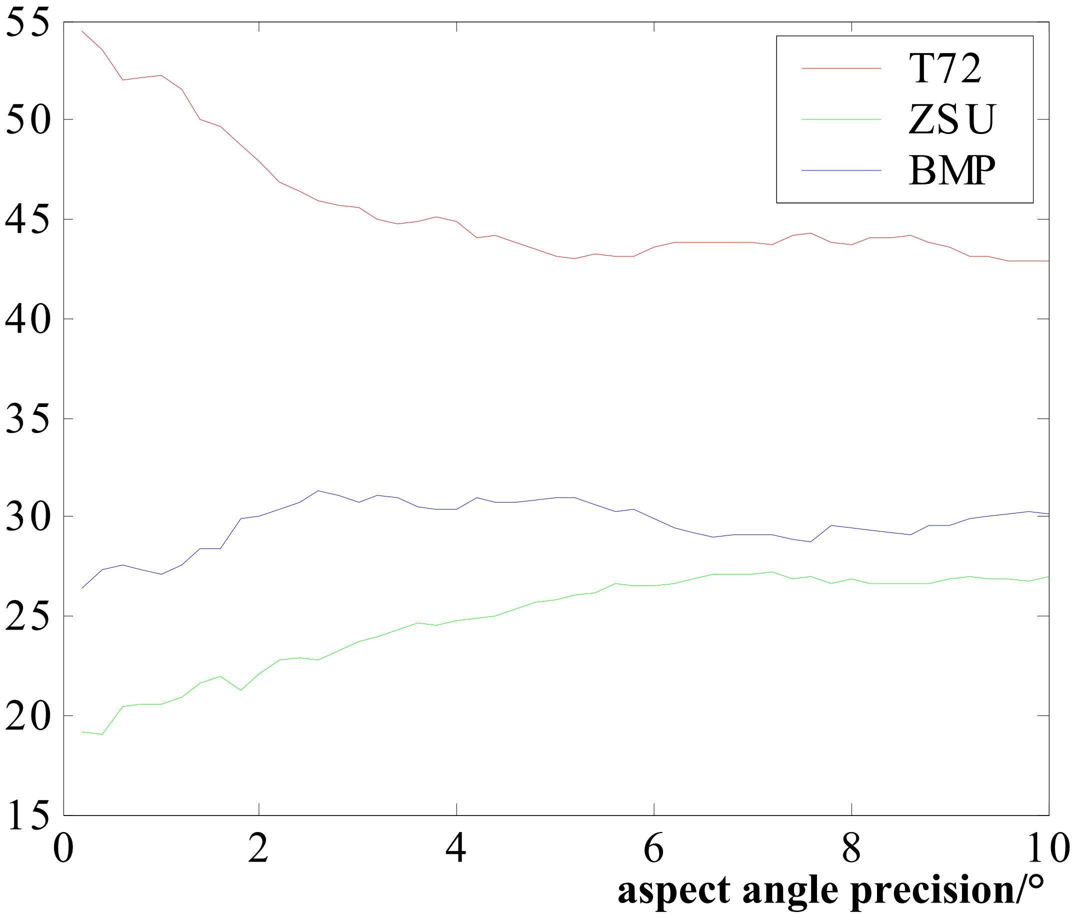
ISAR images are processed with angular increments of about 1/40 of a degree (as a cross-range resolution of 0.2m at 35GHz requires an angular increment of 1.2°, this means overlapping ISAR processing). Thus, an aspect angle interval of 12° gives rise to about 500 templates

Difference between global (360°) and local pdf's



The KSD between global and local pdf's can be as high as 0.5!

Precision of aspect angle determination



P_{cc} (%) of T72 tested against T72 (red), BMP(blue) and ZSU(green), features 2&7

Summary and conclusions

- Two FOMs to quantitatively assess feature robustness were proposed:
  - The Kolmogoroff-Smirnov distance measure between histograms (pdf's) was used to define a metric K_0-K_1 that at the same time allows to quantify intra-class robustness and inter-class separability for an **individual feature**
  - For **sets of several features**, a simple classification approach in connection with a reference confusion matrix provides a distance measure
- It was demonstrated that the target aspect angle is a major source of variabiliy, and that ist independent determination will increase the classification performance